ICES Journal of Marine Science, 2025, Vol. 82, Issue 9, fsaf115
https://doi.org/10.1093/icesjms/fsaf115
Received: 9 March 2025; **revised:** 13 June 2025; **accepted:** 18 June 2025
Quo Vadimus

International Council for the Exploration of the Sea
Conseil International pour l'Exploration de la Mer

Opportunities and challenges for new technologies in seabird population monitoring

Morten Frederiksen [1,*], Kate Layton-Matthews[2], Sophie Bennett[3], Johan H. Funder Castenschiold[1], Marta Cruz-Flores [4], Alice J. Edney[5], Per Fauchald[6], Kirsty A. Franklin[7], Hugo R. Guímaro[8,9], Hannah F. R. Hereward[10], Daniel T. Johnston[3], Benjamin Merkel[11], Sindre Molværsmyr[12], Christophe Sauser[11], Katherine R. S. Snell[13,14], Elizabeth M. Humphreys[3]

[1]Department of Ecoscience, Aarhus University, Frederiksborgvej 399, 4000 Roskilde, Denmark
[2]Norwegian Institute for Nature Research, Sognsveien 68, NO-0855 Oslo, Norway
[3]BTO Scotland, Stirling University Innovation Park, Stirling FK9 4NF, United Kingdom
[4]Instituto de Investigación en Recursos Cinegéticos (IREC), CSIC-UCLM-JCCM, Ciudad Real, Spain
[5]Department of Biology, University of Oxford, 11a Mansfield Road, Oxford OX1 3SZ, United Kingdom
[6]Norwegian Institute for Nature Research, Framsenteret, NO-9296 Tromsø, Norway
[7]RSPB Centre for Conservation Science, RSPB, The Lodge, Sandy SG19 2DL, United Kingdom
[8]British Antarctic Survey, Natural Environment Research Council, Cambridge CB3 0ET, United Kingdom
[9]Department of Life Sciences, University of Coimbra, MARE—Marine and Environmental Sciences Centre/ARNET—Aquatic Research Network, 3000-456 Coimbra, Portugal
[10]BTO Cymru, Thoday Building, Deiniol Road, Bangor, Gwynedd LL57 2UW, United Kingdom
[11]Norwegian Polar Institute, Framsenteret, NO-9296 Tromsø, Norway
[12]Norwegian Institute for Nature Research, Thormøhlens gate 55, NO-5006 Bergen, Norway
[13]Centre for the Advanced Study of Collective Behaviour, University of Konstanz, Konstanz 78464, Germany
[14]Department of Migration, Max Planck Institute of Animal Behavior, Radolfzell 78315, Germany

*Corresponding author. Department of Ecoscience, Aarhus University, Frederiksborgvej 399, 4000 Roskilde, Denmark. E-mail: mfr@ecos.au.dk

Abstract

Monitoring of seabird population size and demography has for decades relied on observer-based methods. While such methods have allowed the accumulation of extensive, standardized time series, while typically involving both volunteer and professional observers, they often suffer from uneven coverage across species and locations, as well as limited replicability. Technological advances, in the form of, for example, visual and/or thermal imagery collected either by permanently situated automated cameras or remote-sensing technology, acoustic data loggers, or automated presence/absence biotelemetry systems, show great potential for overcoming the limitations of observer-based methods and extending coverage of monitoring programmes to more difficult circumstances and species. However, there are challenges and risks associated with the introduction of technology-based monitoring such as initial costs, data storage, post-processing of the large amounts of data, and potential alienation of experienced fieldworkers. We review the issues that agencies responsible for seabird monitoring should consider before introducing technology-based monitoring to complement existing methods, and we provide a set of recommendations and potential future research directions.

Keywords: seabirds; monitoring; technology

Background—the need to monitor seabirds

Seabirds are among the most threatened groups of birds globally (Croxall et al. 2012), with an estimated mean 70% decline in population size over the period 1950–2010 across monitored populations (Paleczny et al. 2015). Collectively, they are exposed to many different threats, the most widespread being predation from invasive species, bycatch in fisheries, and climate-mediated changes, including extreme weather events and changes to bottom-up processes that affect primary productivity (Dias et al. 2019, OSPAR 2023). Moreover, marine ecosystems are under increasing pressure from human activities (Halpern et al. 2008). Many seabird species are relatively easy to observe (though some challenges are discussed below) and their behaviour and demographic performance are strongly affected by prey availability (Montevecchi 1993, Parsons et al. 2008). Therefore, seabirds are often used as indicators of marine ecosystem health (Lescroël et al. 2016). Seabird monitoring also contributes to holistic assessments of marine ecosystems at regional scales (Dierschke et al. 2022, Frederiksen et al. 2022, OSPAR 2023, Thompson et al. 2024). Thus, there is a need for consistent, replicable, and affordable methods for monitoring seabird populations, both to understand their status and to enable large-scale inferences on ecosystem state (Cairns 1987, Piatt et al. 2007, Brisson-Curadeau et al. 2017).

Current approaches

While many single seabird populations have been monitored for many decades using a variety of approaches, the first standardized large-scale, cross-species surveys were established in the 1980s in Britain and Ireland through the Seabird Monitoring Programme (Tasker 2000). This programme served as inspiration for many other countries and regions which, over the next decades, developed their own monitoring schemes such as the Canadian Seabird Colony Monitoring Programme (Gaston et al. 2009) and the Norwegian SEAPOP (Anker-Nilssen et al. 2015). Consequently, to a large extent, monitoring of seabird populations and their demography follows procedures established more than 40 years ago (Walsh et al. 1995). Population size, breeding productivity and annual survival have generally been monitored using direct visual observations (but see below for passive integrated transponders), using the skills of volunteers as well as professional fieldworkers. Although visual-based methodologies often require labour-intensive fieldwork, they typically involve relatively little post-processing, making it feasible to produce annual updates of population size and demography even when using field personnel with limited analytical training.

Despite their widespread success, there are drawbacks to the observer-based methods widely used in seabird monitoring (Mitchell and Parsons 2007). Sources of observer bias are often unknown and challenging to identify in field observations, which can make data and subsequent inference non-comparable and therefore challenging (or impossible) to scale up to broader temporal or spatial scales (Schmidt et al. 2023). An inherent issue with observer-based data is also that they are difficult to document systematically and can have limited reproducibility, although programme-specific protocols have been developed to attempt to address this issue (e.g. the SMP Handbook; Walsh et al. 1995). Finally, given the labour-intensive nature of these methods, sample sizes are generally small, which can lead to imprecise estimates and/or estimates that are only representative of a small area or are based on brief snapshots of observations (Sims et al. 2006).

Another issue is that some species are more challenging to monitor due to limited accessibility of their habitats (e.g. remote offshore islands) and/or the type of nesting site (e.g. burrow/crevice nesters). This can lead to a bias in the species included in an ecosystem-based monitoring programme and, thus, contribute to reduced representativity. Furthermore, a lack of trained volunteers or funds for employing professional staff have limited the implementation of seabird monitoring in low-income countries, resulting in strong biases in our understanding of worldwide variation in seabird population trends (Paleczny et al. 2015).

New approaches

Recently, technological advances have led to the development of a range of increasingly automated, and often also autonomous, monitoring systems, some of which have been tested in seabird colonies (Hentati-Sundberg et al. 2025). These systems include passive or intelligent sensors as well as automated pipelines for data collection, storage and processing. A non-exhaustive overview of examples of such systems being used in seabird monitoring is briefly described here.

Time-lapse photography of cliff-nesting seabirds is increasingly used to measure phenology and breeding success (Merkel et al. 2016, Black 2018, De Pascalis et al. 2018, Edney et al. 2025) and motion-triggered cameras have been employed to re-sight colour-ringed individuals for survival studies and to identify nest predation events (Brides et al. 2018, Johnston et al. 2020). Specifically, in-nest cameras (e.g. Hereward et al. 2021) are useful for monitoring of burrow-nesting species. Surveys using uncrewed aerial vehicles (UAVs) can reach, and so collect data from, remote colonies that are difficult or impossible to access for observer-based methodologies, e.g. sea stacks, steep-sided cliffs, and extensive areas of a flat or inhospitable terrain (Rush et al. 2018, Dunn et al. 2021, Edney et al. 2023). Data from UAVs can be used to measure breeding success and phenology as well as estimate numbers and distributions of birds present (Edney and Wood 2021), ground-nesting and cliff-nesting species for example, but also have the potential to collect data on other biological parameters such as body size and occurrence of disease outbreaks (Tyndall et al. 2024, Stone and Davis 2025). Cameras equipped with thermal imaging capabilities can improve detectability of cryptic and burrow-nesting species, as well as nests that may be difficult to see in visible imagery due to vegetation or terrain (Lee et al. 2019, McKellar et al. 2021). Satellite imagery is being adopted for population estimation of ground-nesting species (Hughes et al. 2011, Fretwell et al. 2012, 2017, 2021, Larue et al. 2024, but see Attard et al. 2025), while acoustic monitoring has been used for counting burrow-nesting species (Buxton et al. 2013, Borker et al. 2014, Oppel et al. 2014). Biotelemetry systems that provide presence/absence information can provide data to parameterize key demographic metrics including survival and dispersal, both of which are major knowledge gaps in seabird ecology, particularly for pre-breeding age classes (Frankish et al. 2021, O'Hanlon et al. 2021, Yanco et al. 2025). Some of these systems have been used for decades, e.g. RFID PIT tags/transponders (Le Bohec et al. 2007, Dehnhard et al. 2014, Horswill et al. 2014) and radio-tracking (Kissling et al. 2015). However, recent advances in automation, through large networks of coordinated receivers and uniquely digitally coded transmitters (e.g. the Motus Wildlife Tracking System: Taylor et al. 2017; ATLAS: Beardsworth et al. 2022; Sigfox: Wild et al. 2023; Icarus: Krondorf et al. 2022), have the potential to enhance data gleaned from ringing, as well as overcoming the limitations and biases associated with observer-based methods. In addition to biotelemetry's primary aim of improving our understanding of animal movement, these emerging technologies can gather information on other data types to provide key insights into causes of changes in population sizes and the demographic rates underlying them (Rishworth et al. 2014)).

Such non-observer-based methods allow for repeated measurements with potentially reduced (time and monetary) investment after the initial setup phase. They also enable more standardized data collection and processing, as well as monitoring of otherwise difficult-to-monitor species (e.g. cavity- and burrow-nesters) or locations. The data collected by these technology-based methods may also be easier to standardize, since images, recordings etc. can be collected automatically at precise schedules, frequencies, and/or locations. Furthermore, methods that do not depend on observer availability can also optimize timing of data collection, which can be an issue when there is annual variability in breeding phenology and if the timing of fieldwork at colonies is inflexible or must be planned far in advance.

Nevertheless, there are also several challenges in the use of technological approaches, such as the costs of equipment as well as data storage and processing. The collection of very large datasets requires development of algorithms for advanced and time-consuming post-processing. This has naturally led to a growing number of studies developing machine-learning algorithms, for example to identify individual birds or nests in images and videos (e.g. Descamps et al. 2011, Williams and DeLeon 2020, Jenkins et al. 2024).

Aim

Although many relevant issues thus have been discussed in the literature, a general overview of opportunities and challenges associated with new technologies in monitoring was lacking. To address this, we held a workshop on ‘How can technology enhance seabird monitoring programmes?’ at the 16th International Seabird Group Conference in Coimbra, Portugal, on 2 September 2024. In this paper, based on discussions at the workshop, we aim to provide a brief assessment of the potential use of new technologies in standardized colony-based seabird monitoring programmes (see the examples in Table 1). Through four focussed questions and a series of examples, we outline the opportunities and challenges associated with these technologies. Our approach is conceptual, and we do not review the suitability of specific technological developments with respect to monitoring seabird demography in detail. Instead, we provide recommendations for how organizations in charge of seabird monitoring programmes may assess whether specific technologies should be added to their toolbox and how to implement them.

What are the benefits of introducing technology-based methods in seabird monitoring programmes?

The expected benefits of integrating new technologies into seabird monitoring can be grouped into two main categories: (1) monitoring of parameters that have been challenging to measure until now and (2) more efficient, less disturbing, and more precise measurements of commonly recorded parameters leading to improved comparability and more comprehensive coverage. Focusing on the latter aspect, technology can allow for scaling up of data collection, enabling more comparable measures between sites. In addition to facilitating more regular and standardized monitoring in existing schemes, technologies can allow us to monitor populations for which it was not possible using observer-based approaches. For example, autonomous recorders could allow monitoring to be extended to situations that previously have been difficult to monitor, such as species which are highly challenging to count visually (e.g. they nest underground, are nocturnal or highly cryptic).

The use of technologies such as UAVs or autonomous recorders can also minimize human disturbance while maximizing data acquisition (Edney et al. 2025). In regions where both volunteers and professional observers are in short supply, a reduced team of observers may deploy recorders in a single visit and return several weeks or months later to collect the data. At the same time, observer disturbance of target birds could be reduced to the time when technologies are deployed (and retrieved if needed) compared to when multiple days, weeks or months of disturbance may be required for observer-based methods. Additionally, the training of personnel for setting up equipment can be less intensive than training an observer to, for example, count a population with high accuracy while minimizing disturbance.

Autonomous detectors can also yield monitoring data that are more standardized (provided open-source algorithms are used to process raw data) and with reduced error or bias compared to observer-based methods (DeLeon et al. 2023, Brusa et al. 2024). While observer-based methods focus on techniques to minimize observer bias, technology-based methods have largely overcome this problem and should rather focus on how to obtain a (statistically) representative design of the observed systems. Raw data could also be stored indefinitely for potential future re-analysis using updated algorithms or for other research purposes. Thirdly, directly transmitted data from autonomous recorders might allow for near real-time assessment of e.g. feeding rates as a proxy of prey availability, as well as increased opportunities for public engagement (Hentati-Sundberg et al. 2023, Purdie 2024, Edney et al. 2025).

What challenges do seabird monitoring programmes encounter when introducing new technologies?

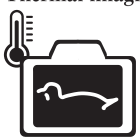
Important challenges associated with the introduction of technology-based monitoring techniques include maturity of specific techniques, data storage requirements, skills and competences as well as financial costs. Innovation in the use of technology has often arisen from the research community, where the focus has largely been around addressing a specific question(s), with less attention to how such methods could be rolled out as monitoring tools. Deciding when a technology is mature or cost-effective enough to deploy on a wider scale is not straightforward, particularly if the variable in question is already covered by observer-based methods. Should new methods supersede or complement previously more common, observer-based methods? Another consideration is to what extent observer-based methods should still rely on volunteers to ensure continuous/future engagement and awareness for the target species through wider participation (https://conservationvolunteers.com.au/positive-impacts-of-citizen-science-for-conservation/). International coordination of data collection will be important, as monitoring parameters should ideally be comparable across national borders to the greatest possible extent (although total comparability is likely not feasible). This is particularly important when combining data from multiple countries to derive indices or other measures of the status of seabirds at a larger regional scale. Other challenges relate to the associated vast increase in data storage and data management requirements, which depends on long-term funding sources (La Sorte et al. 2018). Finally, the costs of developing algorithms to efficiently process the large amounts of data are often underestimated, and there is a risk of an accumulation of unprocessed raw data.

The transition from more traditional observer-based monitoring to implementation of new technologies will also entail a major shift in the required competences of personnel, e.g. related to sensor technology, device deployment on birds, databases, programming and large-scale monitoring design. Implementing a new technology and using it to collect data in the field along with the subsequent processing of those data are two key steps that require quite different skills. In other words, substantial data are being collected with new technologies, at least in some cases, before open-source approaches for processing and incorporating these data are available and implemented in monitoring programmes.

Table 1. Examples of new technologies and their associated benefits, risks, barriers to adoption, and requirements for standardization

Method	Approach, and key variables monitored (*in italics*)	Additional benefits	Risks	Main challenges and barriers	Requirements for standardization
Fixed cameras	Time-lapse and motion-triggered cameras. Autonomous devices record photos of study plots or single nests at fixed intervals. *Relative abundance* *Breeding success* *Phenology* *Survival* *Occurrence*	Minimizes observer disturbance. Within- or between-day variation in numbers present allows calibration of, for example, UAV-based total counts.	Analytical lag. Equipment failure resulting in years without data. Potential bias in site selection.	Power supply (battery or solar). Devices (memory card) often need to be retrieved at end of season. Post-processing of large datasets can be time-consuming and often require development of AI methods.	Best practice guidelines on the design of studies, incl. camera set-up, sampling frequency, etc.
Satellite imagery	Satellite-based imagery is used to estimate the population size of ground-nesting seabird species by acquiring high-resolution images of colonies from space. *Abundance* *Distribution*	Enables monitoring of colonies in remote or difficult-to-access areas. Large-scale, efficient monitoring can assist in mapping large-scale population trends.	High cost of satellite data, particularly for high-frequency monitoring. Potential for data gaps due to weather or satellite scheduling issues. Misinterpretation of data in challenging environments.	Cost and availability of high-resolution satellite imagery. Requires clear skies and good weather conditions for accurate imaging. Temporal and spatial resolution may not capture small species, small colonies or changes in population size immediately. Post-processing of large datasets can be time-consuming.	Standard protocols for image acquisition and analysis. Calibration to ensure accurate population estimates. Consistent imaging schedules and methodologies.
Bioacoustic recording	Autonomous devices record sound in colonies, and species-specific calls are identified subsequently. *Relative abundance* *Phenology* *Breeding success* *Occurrence*	Records all species present. Detection of nuisance species, e.g. non-native mammals.	Device failure Analytical lag	Power supply (battery or solar). Devices (memory card) need to be retrieved to obtain data. The power of a device to detect species' calls may vary with environmental conditions and other factors. Time to process audio data (potentially including the development of new classifiers).	Calibration of bioacoustics-based measures to observer-based ones.
UAVs	Camera-equipped UAVs acquire georeferenced photos or videos of colonies. *Abundance* *Breeding success*	Vastly improved coverage of monitoring of remote and poorly monitored regions.	Analytical lag. Disturbance: Certain species (e.g. terns, gulls) may interact with the UAV or attack it. In-flight failures.	Post-processing of large datasets can be time-consuming and often requires the development of AI methods. Weather conditions (wind, rain) can affect flights and data quality. Data storage and handling. Limited access to drones capable of withstanding extreme environments. Lack of trained pilots. Charging capabilities in the field. High cost. License requirements.	Flight protocols, incl. sortie type (e.g. oblique for cliff-nesting species or line transects for ground-nesting species) and approach procedure. Standardized way of counting from the images, i.e. open-source algorithms.

Table 1. Continued

Method	Approach, and key variables monitored (*in italics*)	Additional benefits	Risks	Main challenges and barriers	Requirements for standardization
Biotelemetry 	Tags deployed on birds provide presence/absence information of individuals, thus collection of data on spatially explicit demographic metrics. *Survival* *Dispersal* *Phenology* *Breeding propensity*	Information on ‘missing years’. (fledging to adult) Year-round spatially explicit monitoring. Bird movements (away from the colony) depending on the availability/location of infrastructure.	Possible tag effects on bird behaviour and demographic rates. Small sample sizes that may not be representative of the wider population. Bias towards high-income countries due to cost.	Size of tags restricting their use on smaller species. Long-term attachment methods and welfare considerations. Refinement of logger attachment methods and training. Data storage, incl. choice of repositories. Cost and maintenance of infrastructure.	Best practice guidelines for the design and implementation of tagging studies, incl. monitoring and reporting for possible device effects.
Thermal imaging 	Handheld, fixed, or UAV-mounted thermal sensors record infrared photos. *Occurrence and abundance* *Distribution and activity* *Monitoring of disease outbreaks*	Useful for: • cryptic species difficult vegetation and terrain • adverse weather conditions, e.g. low light and visibility. • night-based monitoring • reduced background noise for easier AI-automated detection (single-band imagery) • diseased or dead birds can be identified by temperature • detection of mortalities	Lag of standardized postprocessing workflows. Possible disturbance from somewhat close approach due to coarse sensor resolution. Other heat sources, e.g. anthropogenic or natural thermal vents and reflective surfaces.	Requires relatively low ambient temperature, lower than the research object. Post-processing workflow and data conversions can be cumbersome. General coarse resolution (640 × 480) limits the useful operating range. However, fast evolving technology with more powerful sensors on the way (1280 × 1024).	Calibration of sensors and exploration of the effect of different types. Additional analysis of differentiation between species, life stages (chicks and adults) and activities (e.g. breeding and non-breeding).

Rapid developments in artificial intelligence (AI), like machine-learning algorithms, will likely contribute profoundly to more standardized and rapid processing in the coming years. For example, machine learning algorithms have been used to accurately identify and count seabirds in images, much faster than manual image analysis by a human (Hayes et al. 2021, Kellenberger et al. 2021). Building such algorithms requires appropriate computer infrastructure and often large training datasets, although volunteers already involved in seabird monitoring could be trained to annotate images to reduce researcher workload. Machine-learning algorithms might also be viewed as a 'black box' by ecologists, who may be able to use an existing algorithm, but do not have the necessary expertise to re-train and refine a model if the algorithm needs re-training, for example, to improve accuracy on images captured of a new species and/or at a new location. Agencies responsible for seabird management should therefore actively encourage collaboration between ecologists and data scientists to develop suitable algorithms and software in order to streamline development and improve efficiency.

Initial and longer-term maintenance costs of employing new technologies can be high (Tuia et al. 2022). These financial outlays include not just equipment purchase but also, for example, software and the training of the people using the equipment. Furthermore, depending on the specific technology and location, there may be a need for installing receiver stations, new power sources such as photovoltaics, and cabling and data transmission infrastructure (Hentati-Sundberg et al. 2023). Overall costs are thus often higher than expected and careful budgeting is crucial. In some countries, legal requirements may be a limitation to the deployment of some technologies (e.g. licenses to fly UAVs or deploy tags on birds). Some new technologies involve commercially developed equipment, and in such cases built-in proprietary software may prevent or at least hamper standardization of data processing pipelines, e.g. for digital aerial cameras used to count birds or cameras with built-in capacity for individual bird recognition.

What needs to be done to align and standardize data collection?

It is critical that the integrity and continuity of existing monitoring time series are not compromised when new technologies are implemented (Lavers et al. 2019). Old and new methods should therefore be run concurrently, at least at a subset of sites for several years, to allow comparability of old and new methods and ensure a smooth transition and limit risking the integrity of long-term time series (Freeman et al. 2007). This could also provide opportunities for upskilling of volunteers or professional fieldworkers, so that their experience is not lost. Development of, for example, conversion factors (Rodway et al. 2024) between old and new methods could also mean that a two-level approach with more and less intensively monitored sites—as currently used in some monitoring programmes—could be maintained. Furthermore, the application of new technological approaches should be accompanied by standardized protocols of data storage and processing, following the FAIR data principles (findability, accessibility, interoperability, and reusability), to maximize comparability of data, particularly when upscaling to larger spatial scales. There is a strong need for development of standardized protocols for employing new technologies, as well as for data processing. The existing seabird monitoring handbook for Britain and Ireland (Walsh et al. 1995) is due to be revised, and the new version will include protocols for some new technologies. Developing an internationally applicable version of this handbook should be seen as a priority. Careful consideration is also needed around the extent to which existing databases can be adapted to facilitate entry of data collected by new technologies, or whether entirely new databases will have to be designed and built to accommodate such data. Again, the challenges of the two monitoring approaches differ, as observer-based methods are largely centred on minimizing observer bias while technology-based methods need to ensure representative and statistically sound study designs that answer the monitoring goals and associated study questions.

What are the risks of using new technology?

The likely main risk of applying new technology is a too abrupt transition from the established to the new approach. This can lead to several negative consequences, including interruption of existing time series, alienation of fieldworkers who may feel left out, overwhelmed, or undervalued, as well as a weakened connection between fieldworkers and data analysts/modellers. Maintaining traditional approaches at some sites, to ensure intercalibration, may be an opportunity to keep long-standing fieldworkers involved. Furthermore, if proper intercalibration of old and new technologies is not done, spurious trends in monitoring variables may result at a time when evidence-based conservation is more critical than ever. As new technologies gain more traction, it is increasingly important to document by which method each data point was gathered, as some fieldworkers might choose the method they subjectively find the best for each case, and deliver results based on multiple different methods. An additional risk is that new technologies, due to their high initial and in some cases running costs, may contribute to, rather than reduce, the existing imbalances between seabird monitoring in high-income and low-income countries.

Conclusions and recommendations

(1) The introduction of new technologies in seabird monitoring programmes should be carefully planned and budgeted, with a particular focus on identifying medium- to long-term funding. Resources should be allocated in such a way that major national or global data gaps are prioritized. This could take into account any gaps in existing knowledge related to key demographic parameters (e.g. immature/juvenile survival or dispersal rates), species (e.g. those which are hard to monitor due to their breeding ecology), or spatial coverage (e.g. habitats or regions that are poorly covered).

(2) Data storage infrastructure should be in place from the start, and resources should be allocated for long-term data management, post-processing, and analysis. Availability of data for sharing should be secured according to the FAIR principles.

(3) Specific technologies should only be incorporated into monitoring programmes once they are sufficiently mature and standardized.

(4) Both observer-based and new, more technology-focused methods should run concurrently at some sites to ensure

that resulting data are complementary and that old and new approaches are properly inter-calibrated.

(5) Volunteer and professional fieldworkers should be involved in decision-making on the implementation and use of new technologies and, whenever possible, they should be encouraged and receive training to take up these technologies. There will be sites and species that would benefit from the implementation of new technologies; however, where sites are currently monitored, they should be encouraged to retain the use of observer-based methods recognizing the added value of having people on the ground for validation and in terms of knowledge of the site and species of interest.

(6) An international manual of traditional and new seabird monitoring methods should be developed and—as far as possible—methods used should be standardized among countries. Existing international working groups (e.g. OSPAR/HELCOM/ICES Joint Working Group on Marine Birds, Circumpolar Seabird Expert Group) could play a part in encouraging standardization and collaboration.

Potential research directions

Emerging technologies have the potential to greatly increase our knowledge of seabird ecology beyond traditional metrics that have been captured by observer-based surveys and ringing effort. As these technologies become more integrated into seabird monitoring, research should focus on their potential to transform demographic and behavioural studies via cross-disciplinary initiatives and data integration. For instance, this could involve adoption of AI-based data processing of imagery, audio and thermal data to extract fine-scale demographic metrics such as chick provisioning rates. Technologies have the huge advantage of providing year-round data, which is especially advantageous for asynchronous breeders where in-person monitoring is challenging. The combination of demographic and movement data is also critical to understanding the impacts of the full range of pressures experienced on seabirds throughout their annual cycle and the likely impacts, from individuals to populations (O'Hanlon et al. 2023).

New research should also focus on validation of proxies of ecological drivers, e.g. using time-lapse imagery to infer prey availability, where climate proxies are currently often used, or disease outbreaks. Furthermore, coupling different sensor-types, e.g. UAVs with both thermal cameras and acoustics, can enable simultaneous monitoring of multiple species and/or nesting types in previously inaccessible habitats. Biotelemetry and tracking will benefit from continued miniaturization and reduced cost, meaning longer deployments and finer spatio-temporal resolution should allow us to study the non-breeding life stages and population connectivity in more detail. Integrating several data streams into cloud-based platforms will provide opportunities for adaptive monitoring frameworks and early-warning systems. Open-data platforms can also enable greater participatory science, particularly in currently under-monitored areas, contributing to more equitable science. At the same time, automation should also be balanced with fieldworker engagement and involve the co-development of open-source tools and protocols for transparent and standardized monitoring.

Acknowledgements

We thank all workshop participants for their valuable input, and the reviewer and editor for valuable suggestions that helped improve the paper.

Author contributions

Morten Frederiksen (Conceptualization [lead], Writing – original draft [lead], Writing – review & editing [lead]), Kate Layton-Matthews (Conceptualization [lead], Writing – original draft [equal], Writing – review & editing [equal]), Sophie Bennett (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Johan H. Funder Castenschiold (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Marta Cruz-Flores (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Alice J. Edney (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Per Fauchald (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Kirsty A. Franklin (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Hugo R. Guímaro (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Hannah F. R. Hereward (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Daniel T. Johnston (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Benjamin Merkel (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Sindre Molværsmyr (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Christophe Sauser (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), Katherine R. S. Snell (Conceptualization [equal], Writing – original draft [equal], Writing – review & editing [equal]), and Elizabeth M. Humphreys (Conceptualization [lead], Writing – original draft [equal], Writing – review & editing [equal]).

Conflict of interest: None declared.

Funding

None declared.

Data availability

There are no new data associated with this article.

References

Anker-Nilssen T, Barrett RT, Lorentsen S-H *et al. SEAPOP: De ti Første årene, Nøkkeldokument 2005-2014*. Trondheim, Tromsø, Norway: SEAPOP, Norsk Institutt for Naturforskning, Norsk Polarinstitutt & Tromsø Museum, 2015, 58

Attard MRG, Phillips RA, Oppel S *et al.* Feasibility of using very high-resolution satellite imagery to monitor Tristan albatrosses *Diomedea dabbenena* on Gough Island. *Endanger Spec Res* 2025;**56**:187–99. https://doi.org/10.3354/esr01396

Beardsworth CE, Gobbens E, van Maarseveen F *et al.* Validating ATLAS: a regional-scale high-throughput tracking system. *Methods Ecol Evol* 2022;**13**:1990–2004. https://doi.org/https://doi.org/10.1111/2041-210X.13913

Black CE. Spying on seabirds: a review of time-lapse photography capabilities and limitations. *Seabird* 2018;**31**:1–14. https://doi.org/10.61350/sbj.31.1

Borker AL, McKown MW, Ackerman JT *et al.* Vocal activity as a low cost and scalable index of seabird colony size. *Conserv Biol* 2014;**28**:1100–8. https://doi.org/10.1111/cobi.12264

Brides K, Middleton J, Leighton K *et al.* The use of camera traps to identify individual colour-marked geese at a moulting site . *Ringing Migr* 2018;**33**:19–22. https://doi.org/10.1080/03078698.2018.1525194

Brisson-Curadeau E, Patterson A, Whelan S *et al.* Tracking Cairns: biologging improves the use of seabirds as sentinels of the sea. *Front Mar Sci* 2017;**4**:357. https://doi.org/10.3389/fmars.2017.00357

Brusa JL, Farr MT, Evenson J *et al.* Correcting for measurement errors in a long-term aerial survey with auxiliary photographic data. *Ecosphere* 2024;**15**:e4961. https://doi.org/https://doi.org/10.1002/ecs2.4961

Buxton RT, Major HL, Jones IL *et al.* Examining patterns in nocturnal seabird activity and recovery across the Western Aleutian Islands, Alaska, using automated acoustic recording. *The Auk* 2013;**130**:331–41. https://doi.org/10.1525/auk.2013.12134

Cairns DK. Seabirds as indicators of marine food supplies. *Biol Oceanogr* 1987;**5**:261–71.

Croxall JP, Butchart SHM, Lascelles B *et al.* Seabird conservation status, threats and priority actions: a global assessment. *Bird Conserv Int* 2012;**22**:1–34. https://doi.org/10.1017/s0959270912000020

Dehnhard N, Poisbleau M, Demongin L *et al.* High juvenile annual survival probabilities in Southern Rockhopper Penguins *Eudyptes chrysocome* are independent of individual fledging traits. *Ibis* 2014;**156**:548–60. https://doi.org/10.1111/ibi.12167

DeLeon EE, Hook MW, Small MF *et al.* Comparing and combining use of autonomous recording units and traditional counts to monitor Northern Bobwhite. *J Field Ornithol* 2023;**94**:8. https://doi.org/10.5751/JFO-00370-940408

De Pascalis F, Collins PM, Green JA. Utility of time-lapse photography in studies of seabird ecology. *PLoS One* 2018;**13**:e0208995. https://doi.org/10.1371/journal.pone.0208995

Descamps S, Béchet A, Descombes X *et al.* An automatic counter for aerial images of aggregations of large birds. *Bird Study* 2011;**58**:302–8. https://doi.org/10.1080/00063657.2011.588195

Dias MP, Martin R, Pearmain EJ *et al.* Threats to seabirds: a global assessment. *Biol Conserv* 2019;**237**:525–37. https://doi.org/10.1016/j.biocon.2019.06.033

Dierschke V, Marra S, Parsons M *et al.* Marine bird abundance. In: OSPAR (ed.), *The 2023 Quality Status Report for the Northeast Atlantic*. London: OSPAR Commission, 2022

Dunn MJ, Adlard S, Taylor AP *et al.* Un-crewed aerial vehicle population survey of three sympatrically breeding seabird species at Signy Island, South Orkney Islands. *Polar Biol* 2021;**44**:717–27. https://doi.org/10.1007/s00300-021-02831-6

Edney AJ, Danielsen J, Descamps S *et al.* Using citizen science image analysis to measure seabird phenology. *Ibis* 2025;**167**:56–72. https://doi.org/https://doi.org/10.1111/ibi.13317

Edney AJ, Hart T, Jessopp MJ *et al.* Best practices for using drones in seabird monitoring and research. *Mar Ornithol* 2023;**51**:265–80.

Edney AJ, Wood MJ. Applications of digital imaging and analysis in seabird monitoring and research. *Ibis* 2021;**163**:317–37. https://doi.org/10.1111/ibi.12871

Frankish CK, Cunningham C, Manica A *et al.* Tracking juveniles confirms fisheries-bycatch hotspot for an endangered albatross. *Biol Conserv* 2021;**261**:109288. https://doi.org/https://doi.org/10.1016/j.biocon.2021.109288

Frederiksen M, Dierschke V, Marra S *et al.* Marine bird breeding productivity. In: OSPAR (ed.), *The 2023 Quality Status Report for the Northeast Atlantic*. London: OSPAR Commission, 2022

Freeman SN, Noble DG, Newson SE *et al.* Modelling population changes using data from different surveys: the Common Birds Census and the Breeding Bird Survey. *Bird Study* 2007;**54**:61–72. https://doi.org/10.1080/00063650709461457

Fretwell PT, LaRue MA, Morin P *et al.* An emperor penguin population estimate: the first global, synoptic survey of a species from space. *PLoS One* 2012;**7**:e33751. https://doi.org/10.1371/journal.pone.0033751

Fretwell PT, Scofield P, Phillips RA. Using super-high resolution satellite imagery to census threatened albatrosses. *Ibis* 2017;**159**:481–90. https://doi.org/10.1111/ibi.12482

Fretwell PT, Trathan PN. Discovery of new colonies by Sentinel2 reveals good and bad news for emperor penguins. *Remote Sens Ecol Conserv* 2021;**7**:139–53. https://doi.org/10.1002/rse2.176

Gaston AJ, Bertram DF, Boyne AW *et al.* Changes in Canadian seabird populations and ecology since 1970 in relation to changes in oceanography and food webs. *Environ Rev* 2009;**17**:267–86. https://doi.org/10.1139/A09-013

Halpern BS, Walbridge S, Selkoe KA *et al.* A global map of human impact on marine ecosystems. *Science* 2008;**319**:948–52. https://doi.org/10.1126/science.1149345

Hayes MC, Gray PC, Harris G *et al.* Drones and deep learning produce accurate and efficient monitoring of large-scale seabird colonies. *Ornithol Appl* 2021;**123**:duab022. https://doi.org/10.1093/ornithapp/duab022

Hentati-Sundberg J, Berglund PA, Olin AB *et al.* Technological evolution generates new answers and new ways forward: a progress report from the first decade at the Karlsö Auk Lab. *Mar Ornithol* 2025;**53**:21–33.

Hentati-Sundberg J, Olin AB, Reddy S *et al.* Seabird surveillance: combining CCTV and artificial intelligence for monitoring and research. *Remote Sens Ecol Conserv* 2023;**9**:568–81. https://doi.org/https://doi.org/10.1002/rse2.329

Hereward HF, Facey RJ, Sargent AJ *et al.* Raspberry Pi nest cameras: an affordable tool for remote behavioral and conservation monitoring of bird nests. *Ecol Evol* 2021;**11**:14585–97. https://doi.org/10.1002/ece3.8127

Horswill C, Matthiopoulos J, Green JA *et al.* Survival in macaroni penguins and the relative importance of different drivers: individual traits, predation pressure and environmental variability. *J Anim Ecol* 2014;**83**:1057–67. https://doi.org/10.1111/1365-2656.12229

Hughes BJ, Martin GR, Reynolds SJ. The use of Google EarthTM satellite imagery to detect the nests of masked boobies *Sula dactylatra*. *Wildl Biol* 2011;**17**:210–6. https://doi.org/10.2981/10-106

Jenkins M, Franklin KA, Nicoll MAC *et al.* Improving object detection for time-lapse imagery using temporal features in wildlife monitoring. *Sensors* 2024;**24**:8002. https://doi.org/10.3390/s24248002

Johnston DT, Furness RW, Robbins A *et al.* Camera traps reveal predators of breeding Black Guillemots *Cepphus grylle*. *Seabird* 2020;**32**:72–83. https://doi.org/10.61350/sbj.32.72

Kellenberger B, Veen T, Folmer E *et al.* 21000 birds in 4.5 h: efficient large-scale seabird detection with machine learning. *Remote Sens Ecol Conserv* 2021;**7**:445–60. https://doi.org/10.1002/rse2.200

Kissling ML, Lukacs PM, Gende SM *et al.* Multi-state mark-recapture model to estimate survival of a dispersed-nesting seabird, the Kittlitz's murrelet. *J Wildl Manage* 2015;**79**:20–30. https://doi.org/10.1002/jwmg.811

Krondorf M, Bittner S, Plettemeier D *et al.* ICARUS—very low power satellite-based IoT. *Sensors* 2022;**22**:6329. https://doi.org/10.3390/s22176329

Larue M, Iles D, Labrousse S *et al.* Advances in remote sensing of emperor penguins: first multi-year time series documenting trends in the global population. *Proc R Soc B* 2024;**291**:20232067. https://doi.org/10.1098/rspb.2023.2067

La Sorte FA, Lepczyk CA, Burnett JL *et al.* Opportunities and challenges for big data ornithology. *The Condor* 2018;**120**:414–26. https://doi.org/10.1650/condor-17-206.1

Lavers JL, Hutton I, Bond AL. Changes in technology and imperfect detection of nest contents impedes reliable estimates of population trends in burrowing seabirds. *Glob Ecol Conserv* 2019;**17**:e00579. https://doi.org/https://doi.org/10.1016/j.gecco.2019.e00579

Le Bohec C, Gauthier-Clerc M, Gremillet D *et al.* Population dynamics in a long-lived seabird: I. Impact of breeding activity on sur-

vival and breeding probability in unbanded king penguins. *J Anim Ecol* 2007;**76**:1149–60. https://doi.org/10.1111/j.1365-2656.2007.01268.x
Lee WY, Park M, Hyun CU. Detection of two Arctic birds in Greenland and an endangered bird in Korea using RGB and thermal cameras with an unmanned aerial vehicle (UAV). *PLoS One* 2019;**14**:e0222088. https://doi.org/10.1371/journal.pone.0222088
Lescroël A, Mathevet R, Péron C *et al.* Seeing the ocean through the eyes of seabirds: a new path for marine conservation? *Mar Policy* 2016;**68**:212–20. https://doi.org/https://doi.org/10.1016/j.marpol.2016.02.015
McKellar AE, Shephard NG, Chabot D. Dual visible-thermal camera approach facilitates drone surveys of colonial marshbirds. *Remote Sens Ecol Conserv* 2021;**7**:214–26. https://doi.org/10.1002/rse2.183
Merkel FR, Johansen KL, Kristensen AJ. Use of time-lapse photography and digital image analysis to estimate breeding success of a cliff-nesting seabird. *J Field Ornithol* 2016;**87**:84–95. https://doi.org/10.1111/jofo.12143
Mitchell P, Parsons M. *Strategic Review of the Seabird Monitoring Programme*. JNCC, 2007, Accessed 13 July 2025. https://www.researchgate.net/publication/237671514_Strategic_Review_of_the_UK_Seabird_Monitoring_Programme
Montevecchi WA. Birds as indicators of change in marine prey stocks. In: RW Furness, JJD Greenwood (eds.), *Birds as Monitors of Environmental Change*. London: Chapman & Hall, 1993, 217–66.
O'Hanlon NJ, Johnston DT, Cook A *et al.* A crowded ocean: the need for demographic and movement data in seabird conservation. *Ocean Coast Manag* 2023;**244**:106833. https://doi.org/10.1016/j.ocecoaman.2023.106833
O'Hanlon NJ, Wischnewski S, Ewing D *et al.* Feasibility study of large-scale deployment of colour-ringing on black-legged Kittiwake populations to improve the realism of demographic models assessing the population impacts of offshore wind farms. JNCC Report No. 684. Peterborough: Joint Nature Conservation Committee, 2021
Oppel S, Hervías-Parejo S, Oliveira N *et al.* Estimating population size of a nocturnal burrow-nesting seabird using acoustic monitoring and habitat mapping, Nature Conservation. 2014;**7**:1–13.
OSPAR. Quality Status Report (QSR). Marine birds thematic assessment. In: OSPAR (ed.), *The 2023 Quality Status Report for the Northeast Atlantic*. London: OSPAR Commision, 2023
Paleczny M, Hammill E, Karpouzi V *et al.* Population trend of the world's monitored seabirds, 1950-2010. *PLoS One* 2015;**10**:e0129342. https://doi.org/10.1371/journal.pone.0129342
Parsons M, Mitchell I, Butler A *et al.* Seabirds as indicators of the marine environment. *ICES J Mar Sci* 2008;**65**:1520–6. https://doi.org/10.1093/icesjms/fsn155
Piatt JF, Harding AMA, Shultz M *et al.* Seabirds as indicators of marine food supplies: cairns revisited. *Mar Ecol Prog Ser* 2007;**352**:221–34. https://doi.org/10.3354/meps07078
Purdie A. *Alderney's West Coast and Burhou Islands Ramsar Site (and Other Sites) Annual Action Plan 2024*. Alderney, Channel Islands: Alderney Wildlife Trust, 2024
Rishworth GM, Tremblay Y, Green DB *et al.* An automated approach towards measuring time-activity budgets in colonial seabirds. *Methods Ecol Evol* 2014;**5**:854–63. https://doi.org/10.1111/2041-210X.12213
Rodway MS, Bertram DF, Lalach LAR. Mixed metrics and the need to adjust remote-sensing data in the evaluation of key biodiversity areas for colonial-nesting seabirds: an example with glaucous-winged gulls *Larus glaucescens*. *Mar Ornithol* 2024;**52**:341–8.
Rush GP, Clarke LE, Stone M *et al.* Can drones count gulls? Minimal disturbance and semiautomated image processing with an unmanned aerial vehicle for colony-nesting seabirds. *Ecol Evol* 2018;**8**:12322–34. https://doi.org/10.1002/ece3.4495
Schmidt BR, Cruickshank SS, Bühler C *et al.* Observers are a key source of detection heterogeneity and biased occupancy estimates in species monitoring. *Biol Conserv* 2023;**283**:110102. https://doi.org/10.1016/j.biocon.2023.110102
Sims M, Wanless S, Harris MP *et al.* Evaluating the power of monitoring plot designs for detecting long-term trends in the numbers of common guillemots. *J Appl Ecol* 2006;**43**:537–46. https://doi.org/10.1111/j.1365-2664.2006.01163.x
Stone TC, Davis KJ. Using unmanned aerial vehicles to estimate body volume at scale for ecological monitoring. *Methods Ecol Evol* 2025;**16**:317–31. https://doi.org/10.1111/2041-210X.14457
Tasker ML. The UK and Ireland seabird monitoring programme—a history and introduction. *Atl Seab* 2000;**2**:97–102.
Taylor PD, Crewe TL, Mackenzie SA *et al.* The Motus Wildlife Tracking System: a collaborative research network to enhance the understanding of wildlife movement. *Avian Conserv Ecol* 2017;**12**:8. https://doi.org/10.5751/ace-00953-120108
Thompson AR, Swalethorp R, Alksne M *et al.* State of the California Current Ecosystem report in 2022: a tale of two La Ninas. *Front Mar Sci* 2024;**11**:1294011. https://doi.org/10.3389/fmars.2024.1294011
Tuia D, Kellenberger B, Beery S *et al.* Perspectives in machine learning for wildlife conservation. *Nat Commun* 2022;**13**:792. https://doi.org/10.1038/s41467-022-27980-y
Tyndall AA, Nichol CJ, Wade T *et al.* Quantifying the impact of Avian influenza on the Northern Gannet Colony of Bass Rock using ultra-high-resolution drone imagery and deep learning. *Drones* 2024;**8**:40. https://doi.org/10.3390/drones8020040
Walsh PM, Halley DJ, Harris MP *et al. Seabird Monitoring Handbook for Britain and Ireland*. Peterborough: JNCC/RSPB/ITE/Seabird Group, 1995
Wild TA, van Schalkwyk L, Viljoen P *et al.* A multi-species evaluation of digital wildlife monitoring using the Sigfox IoT network. *Anim Biotelemetry* 2023;**11**:13. https://doi.org/10.1186/s40317-023-00326-1
Williams HM, DeLeon RL. Deep learning analysis of nest camera video recordings reveals temperature-sensitive incubation behavior in the purple martin (*Progne subis*). *Behav Ecol Sociobiol* 2020;**74**:1–12. https://doi.org/10.1007/s00265-019-2789-2
Yanco SW, Rutz C, Abrahms B *et al.* Tracking individual animals can reveal the mechanisms of species loss. *Trends Ecol Evol* 2025;**40**:47–56. https://doi.org/10.1016/j.tree.2024.09.008

Handling Editor: Stephen Votier